ON THE IMPACT OF NON-MODAL PHONATION ON PHONOLOGICAL FEATURES

Milos Cernak[1], *Elmar Nöth*[2],
Frank Rudzicz[3], *Heidi Christensen*[4], *Juan Rafael Orozco-Arroyave*[5], *Raman Arora*[6],
Tobias Bocklet[7], *Hamidreza Chinaei*[3], *Julius Hannink*[2], *Phani Sankar Nidadavolu*[6],
Juan Camilo Vásquez[5], *Maria Yancheva*[3], *Alyssa Vann*[8], *Nikolai Vogler*[9]

[1] Idiap Research Institute, Switzerland, milos.cernak@idiap.ch;
[2] Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany, elmar.noeth@fau.de;
[3]University of Toronto, Canada; [4]University of Sheffield, UK;
[5]Universidad de Antioquia Medellín, Colombia; [6]Johns Hopkins University, USA;
[7]Intel, Germany; [8]Stanford University, USA; [9]University of California-Irvine, USA

ABSTRACT

Different modes of vibration of the vocal folds contribute significantly to the voice quality. The neutral mode phonation, often used in a modal voice, is one against which the other modes can be contrastively described, also called non-modal phonations.

This paper investigates the impact of non-modal phonation on phonological posteriors, the probabilities of phonological features inferred from the speech signal using a deep learning approach. Five different non-modal phonations are considered: falsetto, creaky, harshness, tense and breathiness. The impact of such non-modal phonation on phonological features, the Sound Patterns of English (SPE), is investigated in both speech analysis and synthesis tasks. We found that breathy and tense phonation impact the SPE features less, creaky phonation impacts the features moderately, and harsh and falsetto phonation impact the phonological features the most. We also report invariant and the most different SPE features impacted by non-modal phonation.

Index Terms— Phonological features, non-modal phonation, phonological vocoding

1. INTRODUCTION

Pathological speech is characterised by soft volume, monotony, hoarseness, breathiness, imprecise articulation and vocal tremor [1]. The project[1] titled "Analysis by Synthesis of Severely Pathological Voices", conducted at Head and Neck Surgery, UCLA School of Medicine, concluded, that *"No accepted standard system exists for describing pathological voice qualities. Qualities are labeled based on the perceptual judgments of individual clinicians, a procedure plagued by inter- and intra-rater inconsistencies and terminological confusions. Synthetic pathological voices could be useful as an element in a standard protocol for quality assessment..."*

Even if we do not consider analysis and synthesis of pathological voices, non-modal (or aperiodic) phonation of "healthy" speakers poses challenges in current speech technology as well. For example, an American English speaker (labelled BDL) in the ARCTIC speech database [2], often used in current text-to-speech (TTS) research, regularly produces creak in parts of his read sentences. This motivated some recent works to focus on improvements of analysis and synthesis of creaky voices [3, 4].

[1]http://www.seas.ucla.edu/spapl/projects/pathological.html

Recent work on non-modal phonation focuses on detection [5], analysis [6, 7] and synthesis [8] of speech with non-modal phonation. Modern computational paralinguistics tries to 1) get rid of non-modal phonation, or 2) model it, for example, for classification purposes [9]. Non-modal phonation is also studied in sociolinguistics. For example, creaky and falsetto phonations are used more commonly by women. Young adult female voices exhibiting vocal fry are perceived as less competent, less educated, less trustworthy, less attractive, and less hirable [10]. Also falsetto is used more commonly by African American women [11].

However, the production of speech sounds with non-modal phonation has been less studied. Speech sounds can be well characterised by phonological features, and thus, we aim to study in this work the impact of non-modal phonation on phonological features. The goal is to identify the invariant, and the most impacted phonological features, and use these patterns in future work on analysis and synthesis of pathological speech. This characterisation of non-modal phonation using phonological patterns is novel, and not investigated in previous approaches.

For studying the speech with non-modal phonation, we used the read-VQ database [12], the recording of which was inspired by prototype voice quality examples produced by John Laver [13]. Laver's recordings are considered as recordings of non-modal phonation with excellent quality, however only one utterance per the phonation type is available, and thus they are speaker-specific. On the contrary, the read-VQ database contains two male and two female recordings, and is thus speaker-independent. The database covers different non-modal phonations: falsetto, creaky, harshness, tense and breathiness. Analysis of phonological features, the Sound Patterns of English (SPE) features [14], was performed by the PhonVoc toolkit [15]. Consequently, the inferred probabilities of the SPE features, also called phonological posteriors, were used for the re-synthesis of the speech signals. Thus, we used the analysis-by-synthesis approach to study the impact of non-modal phonation on phonological features.

We were first interested in a comparison of the Laver's and read-VQ analyses. Then, the statistically significant differences in modal and non-modal phonological posteriors of the read-VQ data were used to determine invariant and dependent phonological features on non-modal phonation.

The structure of the paper is as follows: Section 2 introduces the non-modal phonation types considered in this work. Section 3 describes experimental setup and evaluation databases, and Section 4 presents results and conclusions of the paper.

2. NON-MODAL PHONATION

We follow Laver's terminology [13] and define the term of voice quality in a broad sense as the characteristic auditory colouring of an individual speaker's voice, and not just in a narrow sense coming from the laryngeal activity. Such a voice quality impacts the production of the speech sounds, and we hypothesised that these changes might be captured by changes of phonological posteriors.

Different modes of vibration of the vocal folds contribute significantly to voice quality. The modal (periodic) phonation, one against which the other modes can be contrastively described, is also called non-modal (aperiodic) phonations.

Breathy and creaky voices belong to the most studied non-modal phonation types. In breathy phonation, the vibration of the vocal folds is accompanied by aspiration noise, which causes a higher first formant bandwidth and a missing third formant [16] due to steeper spectral tilt [17]. In creaky phonation (also referred to as vocal fry, laryngealisation), secondary vibrations occur with lower fundamental frequencies.

Tense voice is produced with higher degree of overall muscular tension involved in the whole vocal tract. The higher tension of the vocal folds does not result in irregularities that are seen in harsh voice. It is characterised by richer harmonics in higher frequencies due to a less steep spectral tilt. Harsh voice is a result of very high muscular tension at the laryngeal level. Pitch is irregular and low, and the speech spectrum contains more noise.

Falsetto voice is the most different with respect to modal voice [13]. The voice is produced with thin vocal folds, that results in a higher pitch voice with a steeper spectral slope.

3. EXPERIMENTAL SETUP

We use our open-source phonological vocoding platform [18] to perform phonological analysis and synthesis. Briefly, the platform is based on cascaded speech analysis and synthesis that works internally with the phonological speech representation. In the phonological analysis part, phonological posteriors are detected directly from the speech signal by Deep Neural Networks (DNNs). Binary [19] or multi-valued classification [20, 21] may be used. In the latter case, the phonological classes are grouped together based on place or manner of articulation. We followed the binary classification approach in our work, and thus each DNN determines the probability of a particular phonological class.

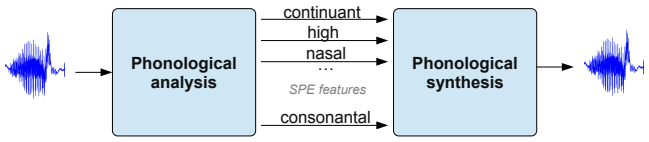

Fig. 1. Phonological analysis and synthesis.

Fig. 1 shows the phonological analysis and synthesis. We used the SPE feature set [14] for training the DNNs for phonological posterior estimation. The mapping from phonemes to SPE phonological classes is taken from [22]. The distribution of the phonological labels is non-uniform, driven by mapping different numbers of phonemes to the phonological classes.

3.1. Training

To train the DNNs for phonological analysis, we first trained a phoneme-based automatic speech recognition system using mel frequency cepstral coefficients (MFCC) as acoustic features. The phoneme set comprises 40 phonemes (including "sil", representing silence) defined by the CMU pronunciation dictionary. The three-state, cross-word triphone models were trained with the HMM-based speech synthesis system (HTS) variant [23] of the Hidden Markov Model Toolkit (HTK) on the 90% subset of the WSJ *si_tr_s_284* set [24]. The remaining 10% subset was used for cross-validation. The acoustic models were used to get boundaries of the phoneme labels, which were mapped to the SPE phonological classes. In total, 13 DNNs were trained as phonological analyzers using the short segment (frame) alignment with two output labels indicating whether the phonological class exists for the aligned phoneme or not. In other words, the two DNN outputs correspond to the target class vs. the rest.

Each DNN was trained on the whole training set. The DNNs have an architecture of $351 \times 1024 \times 1024 \times 1024 \times 2$ neurons, determined empirically based on the authors' experience. The input vectors are 39 order MFCC features with the temporal context of 9 successive frames. The parameters were initialized using deep belief network pre-training following the single-step contrastive divergence (CD-1) procedure of [25]. The DNNs with the softmax output function were then trained using a mini-batch based stochastic gradient descent algorithm with the cross-entropy cost function of the KALDI toolkit [26].

Training of the phonological synthesis starts with preparing input features from the TTS database by performing the phonological analysis using the analysis DNNs. We used the Nancy database provided in the Blizzard Challenge 2011, which consists of 16.6 hours of high quality recordings of natural expressive human speech made in an anechoic chamber. The output features – modelled speech parameters – are extracted by the LPC analysis. Cepstral mean normalisation of the output features is applied before DNN training. The DNN is also initialised by pre-training, and it is trained with a linear output and the mean square error cost function. The synthesis DNN is trained again with the Kaldi toolkit.

3.2. Evaluation data

Prototype voice quality examples produced by John Laver [13] and the read-VQ database [12] were used in the speech analysis and synthesis evaluation described in Section 3.3.

The read-VQ database contains 4 speakers (2 males and 2 females) who were asked to read 17 sentences in six different phonation types: modal, breathy, tense, harsh, creaky and falsetto. Participants were given prototype voice quality examples, produced by John Laver and John Kane, and were asked to practise producing them before coming to the recording session. For the recordings, participants were asked to produce the strong versions of each phonation type and to maintain it throughout the utterance. During the recording session participants were asked to repeat the sentence when it was deemed necessary.

The sentences were chosen from the phonetically compact sentences in the TIMIT corpus [27], four of which contained all-voiced sounds. 451 sentences were chosen in order to obtain a wide phonetic coverage, as it is likely that it can be very difficult for speakers to maintain a constant type of phonation over a long utterance. The recordings with modal phonation were 2.2 minutes long, and the remaining recordings with non-modal phonation were 2.0 minutes long each (i.e., altogether about 12.2 minutes of recordings).

3.3. Analysis and synthesis

Phonological analysis starts by converting speech samples $\vec{x}_n$ with $n \in N$ number of frames in the speech signal into a sequence of acoustic feature observations $X = \{\vec{x}_1, \ldots, \vec{x}_n, \ldots, \vec{x}_N\}$. Conventional cepstral coefficients can be used in this speech analysis step. Then, the analysis realised by DNNs converts the acoustic feature observation sequence X into a sequence of vectors $Z = \{\vec{z}_1, \ldots, \vec{z}_n, \ldots, \vec{z}_N\}$. The vector of phonological parameters $\vec{z}_n = [z_n^1, \ldots, z_n^k, \ldots, z_n^K]^\top$ consists of phonological posterior probabilities $z_n^k = p(c_k|x_n)$ of K phonological features (classes) c_k.

The matrix of posteriors Z thus consist of N rows, indexed by the processed speech frames, and K columns. The following analysis was done on non-silence speech frames of the evaluation data:

$$\mu_k = \frac{1}{N_s} \sum_{n=1}^{N_s} p(c_k|x_n), \forall n \Longleftrightarrow p(c_{\text{SIL}}|x_n) < 0.5, \qquad (1)$$

where c_{SIL} is a posterior probability of silence class being observed, and N_S is the number of non-silence frames. First, modal voice was analysed, followed by other non-modal phonations analysed deferentially (contrastively) to the modal voice:

$$\Delta\mu_k = \mu_k^{\text{modal}} - \mu_k^{\text{non-modal}}. \qquad (2)$$

After obtaining the phonological posterior vectors, we used the posteriors also to re-synthesize the speech signal using the phonological synthesis. The phonological synthesis was trained on Nancy (female) speech with modal phonation, thus impacted (distorted) phonological posteriors caused by non-modal phonation should result in lower quality re-synthesized speech.

4. RESULTS AND DISCUSSION

4.1. Analysis

Fig. 2a shows the analysis of the original Laver's recordings, followed by the analysis of the read-VQ evaluation data in Fig. 2b. By visual comparison of the average differences of Laver's and read-VQ posteriors, we can conclude certain similar patterns, except of breathy voice. Further statistical analysis of the differences between speech with modal and non-modal phonations, allows us to determine invariant, and the most impacted phonological features, listed in Table 1.

Table 1. *The impact of non-modal phonation on phonological features, measured as a positive (+) or negative (−) difference between the mean phonological posteriors of speech with modal phonation, and the mean phonological posteriors with non-modal phonation.*

Phonation	Invariant features	Most different features
Breathy	strident, back, voice, high	+vocalic, +tense, −nasal
Tense	strident, back, round, coronal	−low, −vocalic
Creaky	vocalic, round, high, continuant	+coronal, +conson., +nasal, −back
Harsh	strident, tense	−low, +high, −vocalic
Falsetto	strident, vocalic	+conson., +coronal, +voice, +anterior

4.2. Synthesis

Finally we evaluated synthesized speech of 2 female speakers from the read-VQ database using the Mel Cepstral Distortion (MCD) [28] between original and synthesized speech samples. Lower MCD values indicate higher speech quality of the synthesized speech samples. Fig. 3 shows synthesis results of the read-VQ data.

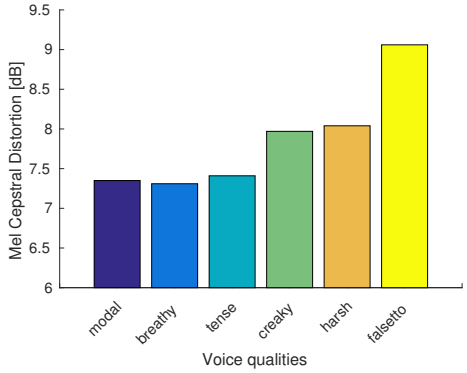

Fig. 3. Quality of non-modal speech synthesis measured objectivelly using Mel Cepstral Distortion in dB. The higher values indicate worse speech quality.

4.3. Discussion

According to Table 1, the strident and less round and back features are more invariant features "resistant" to non-modal phonation, and the rest of the features is heavily impacted. The most impacted features for breathy and tense phonations seem to be related to vowels and nasals (vocalic and nasal features), creaky phonation seems to be related to both vowels and consonants (consonantal and nasal features), and harsh and falsetto phonations impact mostly consonants (consonantal, coronal and anterior). Interestingly, the strident feature is significantly different only in creaky phonation, which indicates its usefulness, for example, in creaky voice detection. On the contrary, the invariant tense feature might indicate harsh phonation. Similarly, the invariant voice feature indicates breathy phonation.

The number of invariant features also indicates the impact on phonological features. While breathy phonation keeps 5 invariant features, harsh and falsetto phonation keep only 2 invariant features. This is confirmed by the synthesis evaluation shown in Fig. 3. Breathy and tense phonation impact the SPE features less, creaky phonation impacts the features moderately, and harsh and falsetto phonation impact the phonological features the most.

In our future work, we plan to apply these invariant and differential patterns in diagnosis and therapy of people with pathological speech. For example, people with Parkinson's disease produce breathy speech. From the presented analysis, we can conclude that the invariant voice feature is the indicator of breathy speech, and the tense posterior features have higher values, which indicate a higher degree of overall muscular tension involved in the vocal tract.

5. ACKNOWLEDGEMENTS

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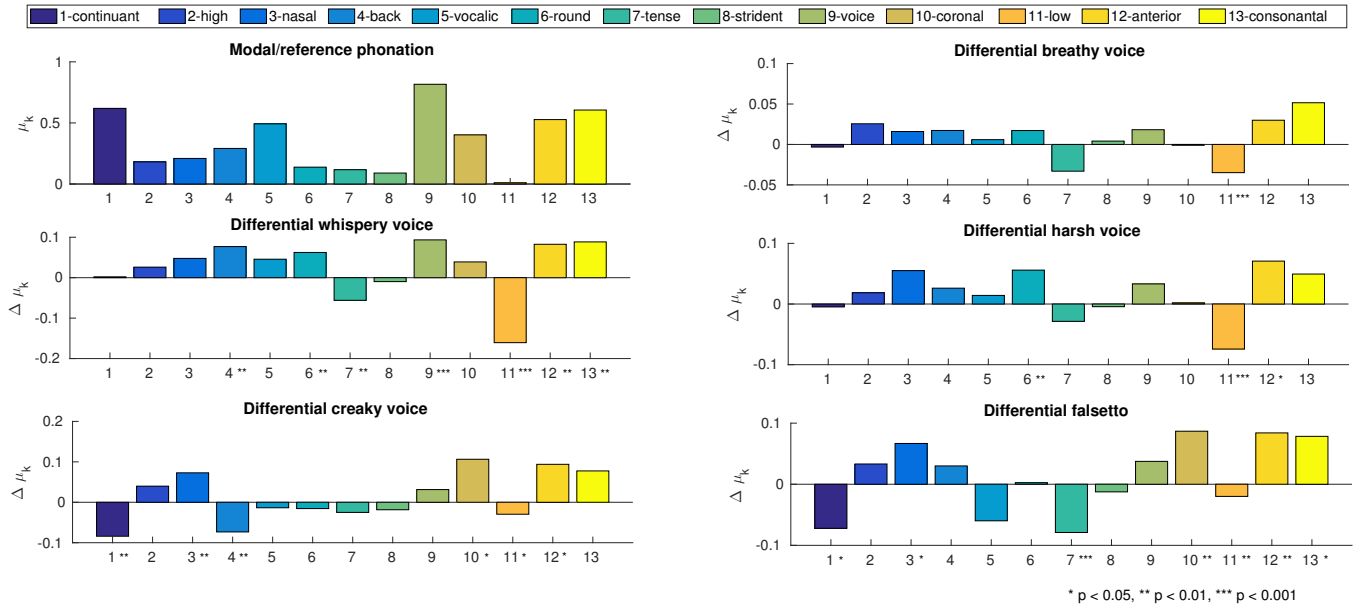
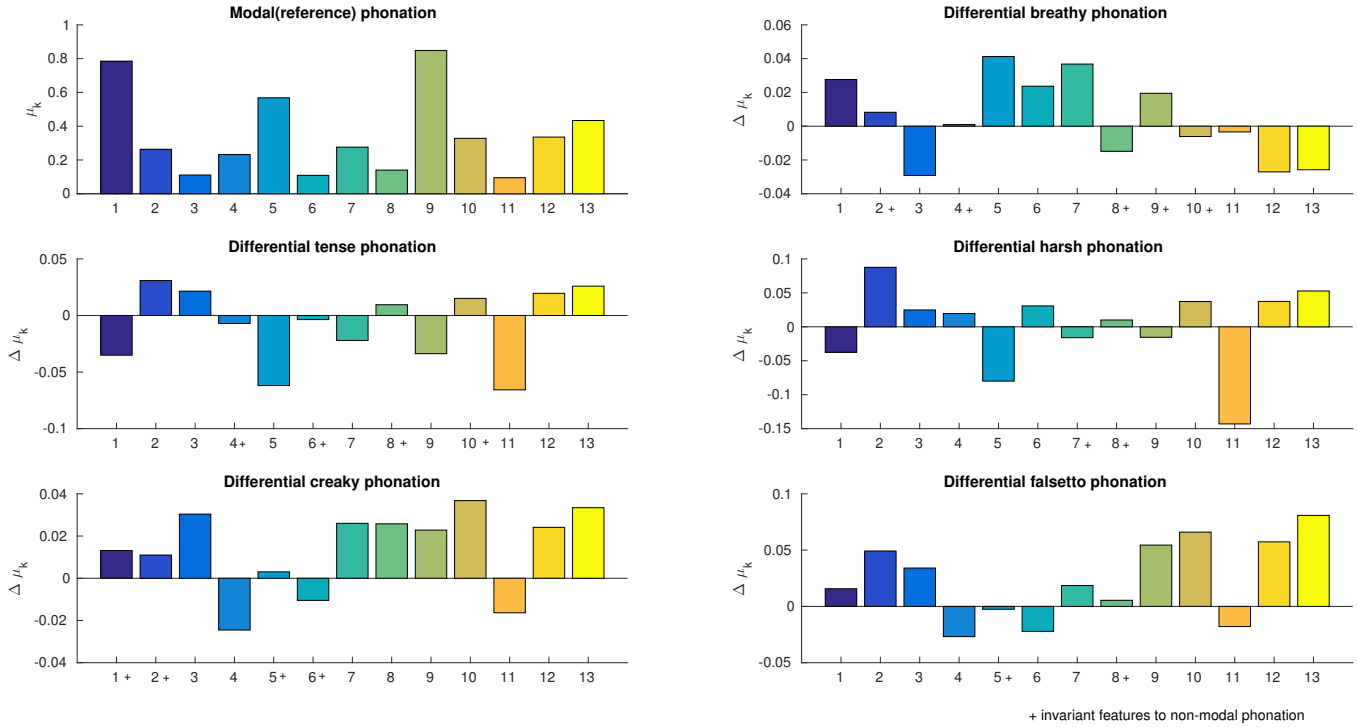


(a) Analysis of the Laver's recordings. The stars next to the indices of the phonological classes indicate statistical significance of difference between the modal and particular non-modal phonation.



(b) Analysis of the read-VQ recordings. The plus next to the indices represent the invariance (where statistical significance of differences is $p > 0.001$), and the rest of the indices represent statistically significant ($p < 0.001$) differences between the modal and particular non-modal phonation.

Fig. 2. Mean modal SPE posteriors μ_k (top-left figures) and differentials $\Delta\mu_k$ of non-modal phonations with respect to the modal voice.

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